Characterizing Multiscale Interaction of Hydrologic Processes Using Multisensor Satellite Data

Praveen Kumar
Department of Civil Engineering
University of Illinois
Urbana, Illinois 61801
e-mail : *kumar1@uiuc.edu*

February, 1998

The objectives of the research are (i) to develop a stochastic-dynamic multiscale model of several key hydrologic variables related to land-atmosphere interaction for assimilating measurements at different scales obtained from satellites; and (ii) to characterize the multiscale feedback interaction between these processes. So far we have developed the multiple scale stochastic-dynamic model and applied it to a scalar valued near-surface soil moisture distribution using data from the Washita'92 experiment. Although the model has been tested for a scalar valued process as a first step, the model development is quite general amd applicable to processes with several interacting variables.

The model developed is motivated by the following three issues:

1. Given measurements at two or more scales (for example, using remote sensing and *in situ* techniques), how can we obtain optimal consistent estimates across scales?

   This problem has been addressed through the development of the multiple scale Kalman filtering algorithm. The key to the algorithm is the development of a state-space model evolving over the scales, i.e., the scale parameter is treated akin to time parameter of the usual state-space models, such that description at a particular scale captures the features of the process up to that scale that are relevant for the prediction of finer scale features. The scale to scale decomposition can be schematically depicted as a tree structure (Figure 1). To describe the model let us use an abstract index λ to specify the nodes on the tree and let $\gamma\lambda$ specify the parent node of λ (see Figure 1). Then the multiple scale stochastic process can be represented as

   $$X(\lambda) = A(\lambda)X(\gamma\lambda) + B(\lambda)W(\lambda). \tag{1}$$

   The term $A(\lambda)X(\gamma\lambda)$ represents the interpolation or prediction down to the next finer level and $B(\lambda)W(\lambda)$ represents new information added as the process evolves from one scale to the next.

   Kalman filtering technique is used to obtain optimal estimates of the states described by the multiple

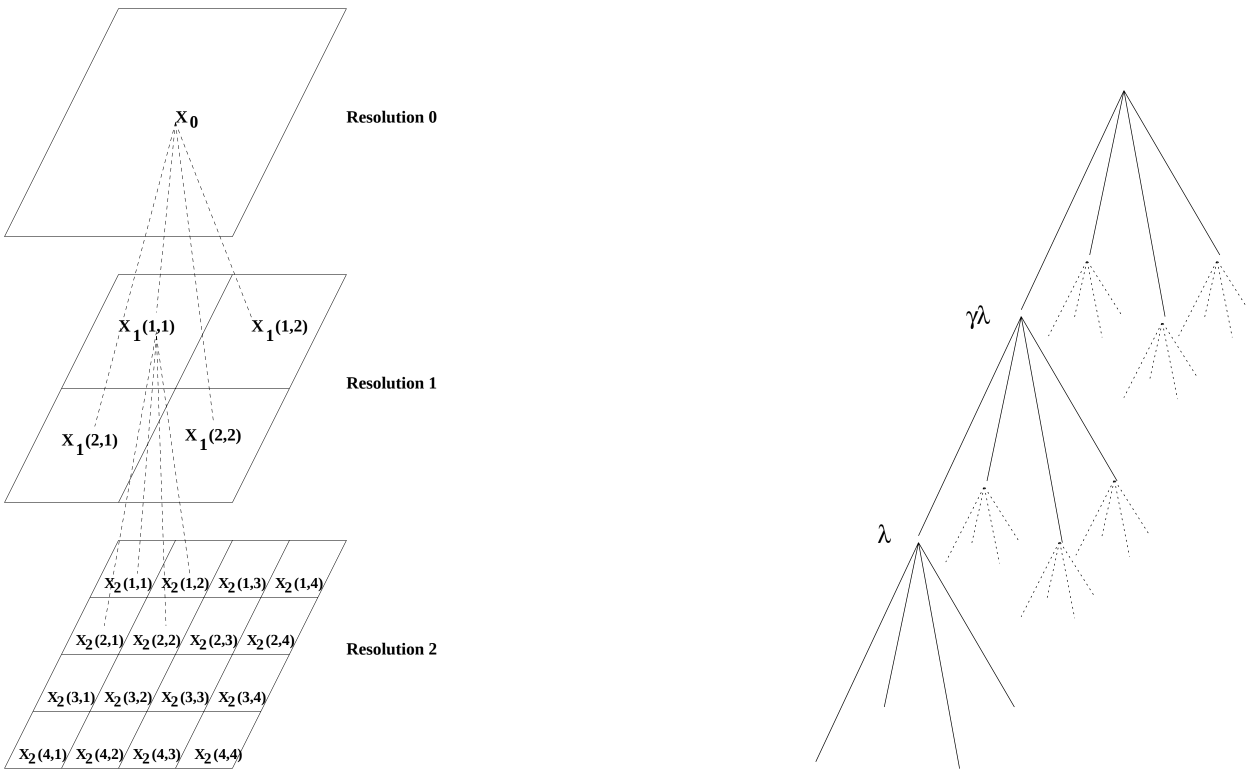


Figure 1: (Left) The structure of a multiple scale random field is shown. The values at various grid locations (i, j) are given as $x_m(i, j)$ where m is the resolution index. At the coarsest resolution ($m = 0$), the field is represented by a single state vector, and generally at the m^{th} resolution there are 4^m state vectors. (Right) Abstract representation of the multiple scale decomposition. The abstract index λ refers to a node in the tree and $\gamma\lambda$ refers to the parent node.

scale model using observations at a hierarchy of scales. This scheme is schematically shown in Figure 2.

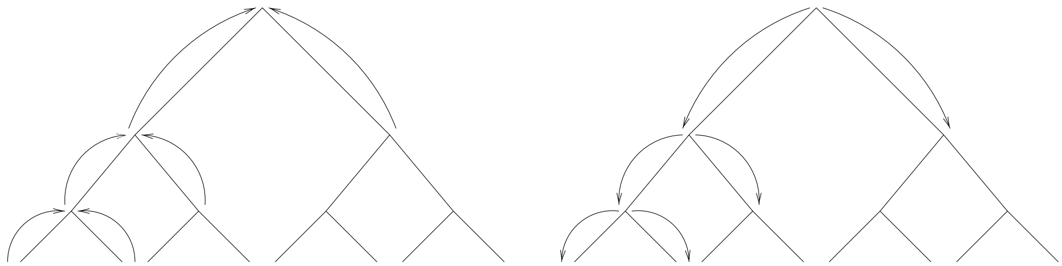
2. Estimation techniques which are based on minimizing a cost function, typically involving the variance, underestimate the variability and the resulting estimated field is smoother than the true field. Therefore, conditional simulation rather than estimation, is used to characterize the variability of the underlying field. The random fields obtained by this technique preserve the observed values where they are known and at the same time simulate the intrinsic fluctuations at other locations that are consistent with the mean and the covariance of the process. Given the wide utility of conditional simulation technique for the usual one- and two-dimensional processes, how can we develop an algorithm for the multiple scale framework?

   This problem as been solved through the development of a multiple scale conditional simulation algorithm. This allows us to construct synthetic fields that are representative of the intrinsic variability of the process. This uses a multiple scale model for the estimation error process whose parameters can be explicitly computed. The conditional model reduces to the unconditional simulation model in the absence of measurements, as should be expected. The conditionally simulated fields can then be used for several applications such as assessment of subgrid variability, inputs to physical models or design of sampling strategies etc. These are of significant importance for random fields such as soil-moisture which show significant variability even at very small scales.

3. Given measurements at some large scale, how do we obtain simulated fields at smaller scales that are consistent with the measurements at the larger scale? This may be considered as a scale extrapolation problem. The motivation for this problem is to provide a methodology to infer subpixel variability from satellite based instruments which provide measurements at a resolution of the order of tens of meters to kilometers.

   This problem has also been solved and implemented for soil-moisture fields. A state-space model relating the soil-moisture with the underlying soil hydrologic properties is developed (see Figure 3) for obtaining conditionally simulated random fields at scales smaller than those at which measurements are available. The soil moisture state is modeled as a mean-differenced fractional Brownian or fractal process. Results using this technique for the Washita'92 data are shown in Figure 4.

In addition we are investiagting the relative roles of heterogeneity (the variations in soil-moisture due to the underlying systematic variations of topography and soil-hydrologic properties) and stochastic variability (variability not accounted for by the systematic variations) in the spatial organization of soil-moisture at large scales. It is found that the variability due to the soil texture variation (systematic varaiation) is far greater than either due to landuse or topographic index. In fact the mean values of soil moisture in different topographic index quantiles are indistinguishable.



(a) Upward Pass

(b) Downward Pass

Figure 2: Schematic of two-pass estimation in the multiple scale framework. First the upward pass propogates information up the tree. At each tree node the estimate incorporates all measurements on that node (if present) and its descendants. Then during the downward pass the information is propogated down the tree. The estimates at each tree node are now based on information on all nodes on the tree.

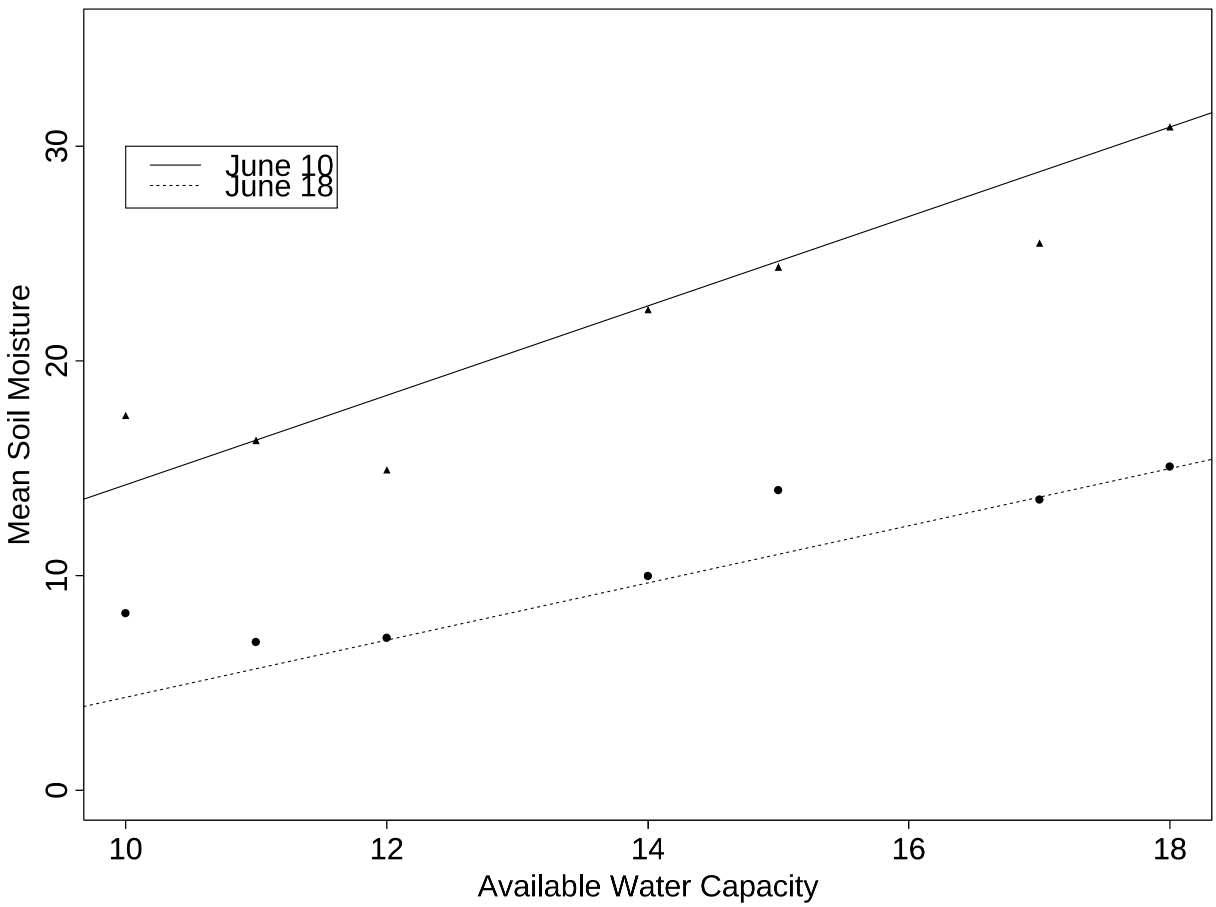


Figure 3: Figure showing the dependence of mean soil moisture for each hydrologic group on the available water capacity for different hydrologic groups for the June 10 and June 18, 1992 datasets.

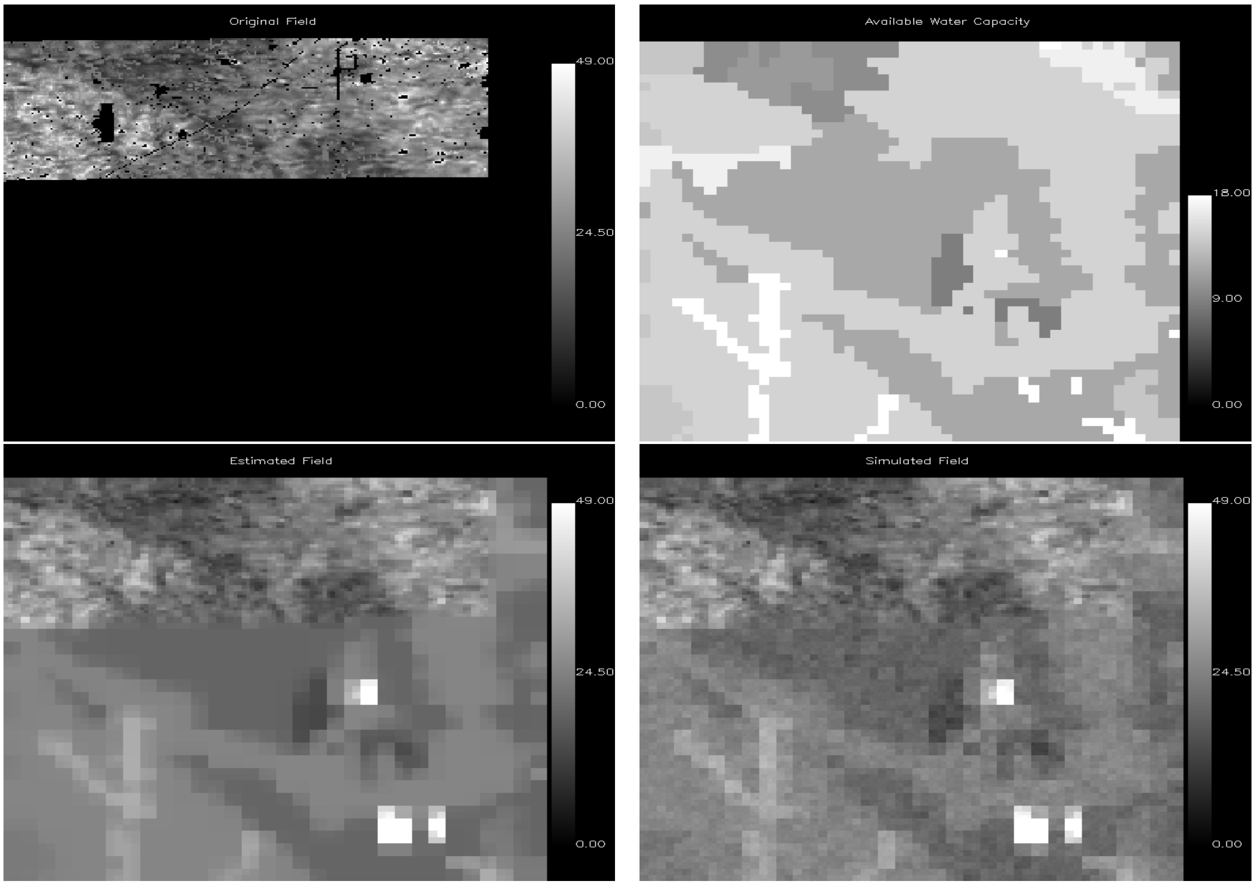


Figure 4: Estimation and conditional simulation of soil-moisture outside the measurement domain where only AWC information is available (June 10, 1992) (a; Top, left) Original field at 256×256 grid. Notice that the actual measurements lie on a subset of the domian.(b; Top, right) Available water capacity field for the domain obtained from the STATSGO database. (c; Bottom, left) Estimated field (d; Bottom, right) Conditionally simulated field.